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Impacts of climate change and land use on the development of nutrient criteria

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ABSTRACT

Numeric criteria are crucial for controlling cultural eutrophication and for protecting current and future water quality. Anthropogenic climate change and the modification of land use have the potential to influence the development of nutrient criteria. In this study, stressor-response models, land use-nutrient regression models, and terrestrial ecosystem health states were used to determine the criterion values of total nitrogen (TN), total phosphorous (TP), and chlorophyll a (Chl *a*) using field data from lakes and reservoirs in Heilongjiang Province. Analysis of covariance and nonlinear regressions were used to quantitatively characterize the impact of climate change on the development of nutrient criteria. The results indicated that there were no significant differences in the nutrient criteria obtained by the various methods. Climate change factors (such as temperature, precipitation, and wind speed) are predicted to influence the relationships between nutrients and Chl *a*, as well as land use and nutrient concentrations, as climate change persists. Climate change should be considered during the development of nutrient criteria, as climate-driven change and achieving a desired water quality without the threat of eutrophication in the future will require stricter nutrient criteria than those needed under the current climate conditions.

1. Introduction

Nutrient criteria are the basis for water pollution control and indicate the enrichment status of waters in the absence of significant human disturbance (Bouleau and Pont, 2015; US EPA, 2000). The development of numeric criteria is important for assisting regulators, controlling cultural eutrophication, evaluating the influence of human activities on aquatic ecosystems, and protecting water quality and aquatic life integrity (Hawkins et al., 2010; US EPA, 2010).

Nutrients such as nitrogen and phosphorus are not toxic to aquatic organisms or humans at low levels, and the dose-response relationships which represent the toxic effects of chemical pollutants using simple laboratory studies have restricted the availability to nutrient criteria development (Huo et al., 2013; Lamon and Qian, 2008). Statistical analysis based on large amounts of observation data can provide theoretical information to support the development of nutrient criteria (Sun et al., 2017). Three types of statistical analyses have been recommended for developing nutrient criteria, namely, the reference condition approach, mechanistic modeling, and stressor-response analysis (Hausmann et al., 2016; US EPA, 2010).

Water quality conditions are widely influenced by the entire watershed, and no lake watersheds are negligibly affected by land use and climate change resulting from intensive human activities. Land use patterns and climate change can have extensive impacts on the development of nutrient criteria, which makes determining numeric nutrient criteria difficult. Changes in land use can influence the ability of soil to mitigate external interferences, which directly impacts the quality of receiving water (Zhang et al., 2012). The spatial distribution of land use affects the connectivity between pollution sources and sinks because there are different contamination transport and transformation capacities in the different land use types (Van Rompaey et al., 2007). The human modification of natural landscapes associated with soil degradation, changes in water flow and quality, and other impacts may alter ecosystem functions and decrease biodiversity (Kissinger and Rees, 2010).

Recently, climate change has altered the relationship between

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nutrients and primary productivity. Climate change is expected to modify ecological responses in the ocean and may potentially have important effects on ecosystem services (Henson et al., 2017). Climate change would enhance cyanobacterial blooms as a result of increasing nutrient inputs via heavy rainfall, longer and more stable periods of thermal stratification, and increasing water temperatures, all of which are conducive to the growth of cyanobacteria relative to other algae (Hayes et al., 2015; Paerl and Huisman, 2009; Paerl and Paul, 2012). Water temperature is highly correlated with primary productivity and affects cyanobacterial development, which regulates the production of carbohydrates, the synthesis of gas vesicles and the rate of photosynthesis in algal cells (Wang et al., 2016a,b). Furthermore, rising temperatures are expected to increase the rate of mineralization of soil nutrients and deoxygenation at the lake sediment surface and the rate of nutrient release into overlying water (Kosten et al., 2012). Due to greater nutrient inputs into waterbodies and flushing after rainfall, rainfall at various intensities and frequencies can affect cyanobacterial biomass dynamics (Reichwaldt and Ghadouani, 2012). Intense precipitation events supply aquatic ecosystems with 80% of annual P loads in watersheds dominated by agriculture (David et al., 2006; Hayes et al., 2015). High surface concentrations of cyanobacterial cells and vast bloom areas usually occur under weak wind conditions because gas vesicles are negatively correlated with increasing wind and waves (Cao et al., 2006; Wu et al., 2015). Extreme weather events (EWEs), such as heavy rainfall events and large storms, may increase primary productivity and/or the resuspension of benthic cyanobacteria and promote the formation of cyanobacterial blooms (Chen and Tang, 2012; Robson and Hamilton, 2003; Zhu et al., 2014). Hence, land use patterns and climate change indicators should be considered when developing nutrient criteria.

However, little research has been conducted regarding the effect of future climate change on nutrient criteria development. In this paper, the criterion values for total nitrogen (TN), total phosphorous (TP), and chlorophyll a (Chl *a*) were developed based on the combined consideration of stressor-response models, land use-nutrient regression models, and terrestrial ecosystem health. The purpose is to examine how climate change indicators and land use patterns can influence the development of nutrient criteria. To achieve this objective, (1) stressor-response models, including a linear regression model (LRM), a classification and regression tree (CART) model, and changepoint analysis (CPA), were applied to determine nutrient criteria; (2) a regression model involving land use and nutrients was used to develop nutrient criteria; (3) the terrestrial ecosystem health status of the studied lake watershed was assessed to verify the reliability of the criterion values; and (4) climate change indicators were applied to infer the impact of climate change on the development of nutrient criteria in Heilongjiang Province.

2. Materials and methods

2.1. Study area

Heilongjiang Province (121°11′-135°05′E, 43°26′-53°33′N) is a temperate continental monsoon climate zone located in northeastern China. The lakes (area > 1 km^2) cover a total area of approximately 3241.3 km^2 (Liu, 2011) and are mainly distributed in the watersheds of the Heilongjiang River, Songhuajiang River, and Wusulijiang River. Some lakes and reservoirs in this area have suffered from serious eutrophication in recent decades, and environmental quality continues to decline with the rapid economic development in Heilongjiang Province. In this study, 21 water bodies were investigated to establish nutrient criteria in this region (Fig. 1). The information regarding the 21 studied lakes and reservoirs is listed in Table S1 (Supporting Information, SI). Meteorological data show that the annual mean temperature of the land surface (Tm) in Heilongjiang Province increased significantly from 1961 to 2016, and the heating rate was 0.35 °C per decade (Fig. 5(a)). The warming rate of the land surface Tm in China was 0.23 °C per decade (National Climate Center, 2016), indicating that Heilongjiang Province is sensitive to climate change.

2.2. Data sources and data quality

The TN, TP, and Chl *a* concentrations; land use patterns; and climate change indicators were collected for each studied lake watershed. Data on the nutrient and Chl *a* concentrations in the lakes of Heilongjiang Province were obtained from the ambient lake monitoring network administered by the Department of Environmental Protection of Heilongjiang Province. In total, 21 water bodies were selected for this analysis, which spanned the period from 1988 to 2015. The TN, TP, and Chl *a* indices were analyzed in a laboratory using the standard testing procedures recommended by the Ministry of Environmental Protection of China (PRC MEP, 2002). The annual mean concentrations of the aforementioned variables for all samples from each lake were used as the dependent variables.

Geographic information system (GIS) software was used to extract lake watersheds, interpret land use data, and assess soil erosion. Land use data from Heilongjiang Province at a resolution of 30 × 30 m were obtained from the Institute of Geographic Sciences and Natural Resources Research (IGSNRR, Chinese Academy of Sciences) for five periods (1988, 1995, 2000, 2007, and 2015). The original land use was further grouped into six main categories: (1) cropland, including paddy fields and dry land; (2) forestland; (3) grassland; (4) water bodies, including rivers and sandy beaches; (5) urban and rural land, including urban land, rural residential areas, and other construction lands; and (6) unused land. ArcGIS 10.2 Desktop GIS software was used to calculate the area corresponding to each land use type within the region. The percentages of cropland, forestland, grassland, water bodies, urban and rural land, and unused land in the watershed were abbreviated as PC, PF, PG, PW, PUR, and PUN, respectively.

Climate change indicators, such as annual Tm (°C), annual precipitation (Pre, mm/year), annual mean wind speed (Win, m/s), and annual relative humidity (Rhu, %), in Heilongjiang Province were obtained from the CN05.1 dataset, which was constructed by the “anomaly approach” during interpolation based on many station observations (~2400) in China (Wu and Gao, 2013; Xu et al., 2009).

2.3. Methods for establishing nutrient criteria

2.3.1. Stressor-response models

Stressor-response models incorporating LRM, CART, and CPA were used to estimate and interpret numeric nutrient criteria to handle both nitrogen and phosphorus pollution (US EPA, 2010). The LRM method evaluates the linear relationship between one response variable and more than one stressor variables. A LRM can be further split into simple linear regression (SLR) and multiple linear regression (MLR) models. The results of SLR are two coefficients specifying the intercept and slope of a straight line representing the modeled relationship between the two variables (US EPA, 2010). MLR is useful for modeling the combined effects of different nutrients and other environmental factors that influence the response variable (Huo et al., 2014). The complementary equations for LRM can be seen in S1 section in the SI.

CART is beneficial for environmental and ecological research because it can predict interactive effects, handle both continuous and discrete variables, and establish a hierarchical structure (Qian and Anderson, 1999; Qian, 2009). CART analysis does not need to assume the possible distribution of the predictor variables, and it can use numerical data that are highly skewed or multimodal, as well as categorical predictors. This approach shortens the time required to determine whether variables are normally distributed and to convert non-normally distributed data (Qian and Anderson, 1999). The complementary algorithm methods and equations for CART model can be seen in S2 section in the SI.

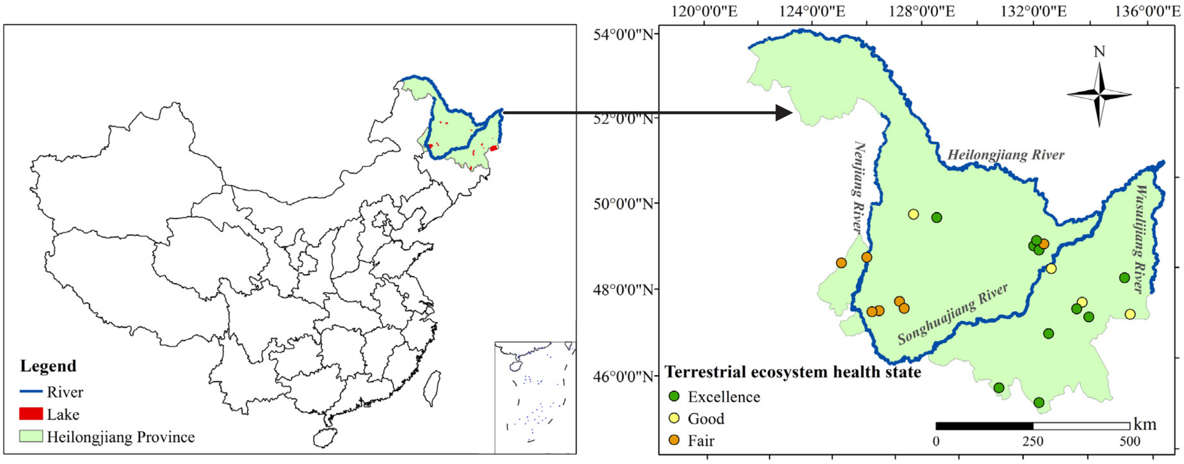


Fig. 1. The locations and terrestrial ecosystem health states of the lakes in Heilongjiang Province.

CPA is applied to calculate the locations of thresholds or changepoints in bivariate nonlinear stressor-response relationships (US EPA, 2010). If observations from multiple sites are ordered along a gradient, a threshold or sudden change in the statistical attributes of the dependent variable will occur in the relationship between a stressor variable and a response variable. CPA, which is based on nonparametric CPA (nCPA) and Bayesian hierarchical modeling (BHM), can therefore be used to determine the point at which the change occurs (Breiman et al., 1984; Qian et al., 2003). In this study, the response variables can be approximated by a normal distribution, and a Gibbs sampling procedure was used to estimate the parameters (Qian et al., 2004). Before conducting CPA using the BHM method, specific information on the distribution of the response variable is required to determine whether the distribution satisfies the assumption of normality. The complementary algorithm methods and equations of CPA can be seen in S3 section in the SI.

2.3.2. Land use-nutrient regression model

Land use-nutrient regression models were used to examine the general correlations among the nutrients (or Chl *a*) and land use to derive the criterion concentrations. The land use percentages were used as the predictor variables, and TN, TP and Chl *a* were used as the dependent variables. CART analysis was first used as a variable selection method to identify important land use patterns associated with variations in nutrients and Chl *a* (Huo et al., 2015b). The coefficient of determination (R^2) in the land use-nutrient regression model was used to measure how well the land use percentages explained these variations. The best regression models were employed to determine nutrient and Chl *a* concentrations. In this extrapolation, the variability was characterized using a 90% confidence interval (CI).

2.3.3. Terrestrial ecosystem health assessment method

The weights of the terrestrial ecosystem health assessment indicators were assessed according to an analytic hierarchy process. The equation for terrestrial ecosystem health assessment was as follows:

$$I_L = \sum_{i=1}^{n} W_i \times X_i$$

where I_L is the health index of the terrestrial ecosystem, W_i is the weight of the ith assessment indicator, and X_i is the value of the ith assessment indicator. Based on the value of I_L, the health status of a terrestrial ecosystem can be classified as excellent ($I_L \geq 80$), good ($60 \leq I_L < 80$), fair ($40 \leq I_L < 60$), poor ($20 \leq I_L < 40$), or bad ($I_L < 20$) (PRC MEP, 2013). The specific method for assessing terrestrial ecosystem health referred to the previous literature (Ma et al., 2016).

The concentrations of TN, TP, and Chl *a* in Heilongjiang lakes and reservoirs were log10 transformed to ensure that the data distributions did not produce intercept estimates that were less than zero (Dodds, 2006). The R function rpart was used to calculate the nodes of the CART model and the changepoint of nCPA, and the R function bootstrap was applied to evaluate the 90% CI of each threshold with 1000 random permutations (R 3.0.2, http://cran.r-project.org/bin/windows/base/). Matlab software (R2007b, The MathWorks company, US) was used for the BHM analysis and the calculation of the 90% CI for the changepoint. Analysis of covariance (ANCOVA) was performed using SPSS 16 to test for significant differences among climate change factors while accounting for the effects of nutrients on Chl *a*, as well as land use variables on water quality.

Reservoirs have characteristics similar to those of lakes in terms of nutrient ecological effects and human activities; hence, similar methods can be used to determine the reservoir nutrient criteria.

3. Results

3.1. Nutrient criteria development by the stressor-response model

3.1.1. The linear regression model

The stressor-response models are based on the assumption that lakes and reservoirs in Heilongjiang Province are likely to have similar Chl *a* responses to nutrient variations. The annual values of Chl *a*, TP and TN were collected from the study region to build the LRM, and datasets from April to September were analyzed to estimate seasonal effects. The SLR models of lgChl *a* using lgTP or lgTN as predictor variables are shown in Fig. 2 and Table 1. CIs (90%) were used to describe the inherent uncertainty in estimating a mean response value when deriving criteria from the LRM.

Significant positive correlations ($p < 0.001$) were found between lgChl *a* and lgTP, implying that reductions in lgTP are accompanied by those in lgChl *a* (Table 1 and Fig. 2). The p-value of lgTN was much larger than 0.10, which indicated the lack of a good linear relationship between lgChl *a* and lgTN, and lgTN did not explain variations in lgChl *a* in Heilongjiang Province. The hypothesis that 5 μg/L Chl *a* concentration was served as the criteria of the response variable for lakes and reservoirs in this region to satisfy the drinking water use. The upper 90% CI intersected Chl *a* = 5.0 μg/L at TP = 0.041 mg/L, the lower CI intersected at TP = 0.061 mg/L, and the mean relationship intersected at TP = 0.051 mg/L (Arrows A, C, and B in Fig. 2(a), respectively). The CIs of SLM for TP in the lakes and reservoirs in Heilongjiang Province were 0.041–0.061 mg/L (annual data) and 0.042–0.066 mg/L (data from April to September).

Furthermore, lgTN and lgTP were simultaneously used to construct

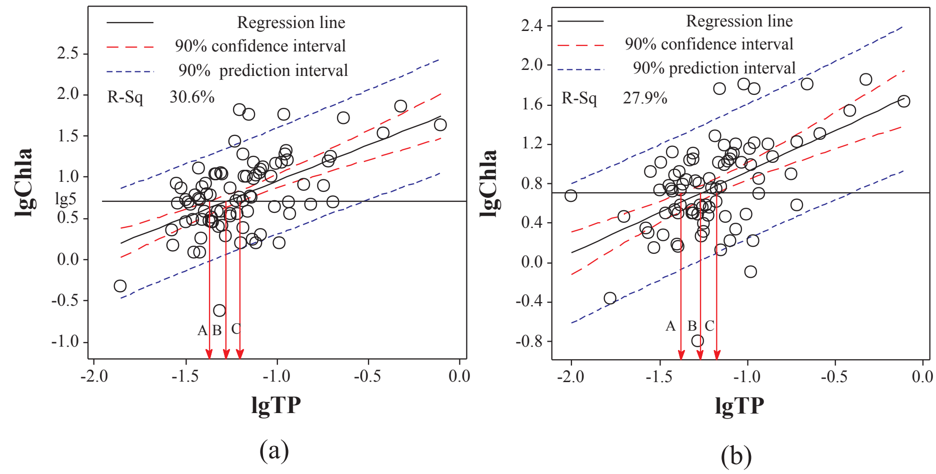


Fig. 2. The simple linear regression models between lgTP and lgChl *a* for Heilongjiang Province.

a multiple regression model for lgChl *a* in the lakes and reservoirs of Heilongjiang Province. This model was not effective or useful for accurately predicting future conditions in this region because the p-value of lgTN was much greater than 0.05 (Table 1). This result indicated a nonlinear relationship between lgChl *a* and lgTN, and nonlinear models, such as CART and CPA, were developed to establish nutrient thresholds.

3.1.2. Classification and regression tree analysis

CART was adopted to identify important variables that influenced the variation in the response variable in Heilongjiang Province. The observed lgChl *a* concentration was used as the response variable. The lgTP and lgTN concentrations were selected as potential predictor variables in each model. The datasets from April to September were also analyzed to obtain estimates that represented the seasonal effect. The final models were selected based on their predictability, which was simulated by cross-validation, and are presented graphically. The variable selected first was the most important one or the one with the greatest effect on the lgChl *a* concentration. CART analyses indicated a hierarchical structure between nutrient and lgChl *a* concentrations (Fig. 3). The standard deviation (SD) of the Chl *a* concentration data was used as a measure of dispersion.

The variability in the lgChl *a* concentration in this region was driven primarily by the lgTP concentration (Fig. 3). The mean Chl *a* concentration for TP concentrations less than 0.058 mg/L was 4.406 μg/L (SD = 2.294), and the mean Chl *a* concentration at higher TP concentrations was 16.379 μg/L (2.870). For TP concentrations higher than 0.058 mg/L, TN was the second most important variable. The lower panel of Fig. 3 shows boxplots of Chl *a* concentrations within each of the terminal nodes. Only the first two splits included in the terminal model demonstrated that further splits would not reduce the relative predictive error of the model or increase the predictive correlation coefficient (R^2).

From April to September, TP was also the decisive variable that influenced Chl *a* concentrations in this region (Fig. 3), indicating that the P-limiting conditions were relatively stable with seasonal variations. Nutrient node values were frequently higher than the annual values from April to September. This pattern likely stemmed from fluctuations in complex environmental factors, such as the increasing water quantity, deteriorating water quality, and increasing Tm from April to September. These factors changed the response relationships between nutrients and algal growth. Hence, seasonal variability must be considered when defining nutrient criteria. The node concentrations ranged from 0.058 mg/L to 0.062 mg/L for the TP concentration and from 0.725 mg/L to 0.908 mg/L for the TN concentration.

The CART models were not developed to predict Chl *a* concentrations. However, these models can provide valuable information for water quality management. For example, the boxplots of Fig. 3 show that a large variance in the Chl *a* concentration corresponds to high TP and high TN concentrations. Hence, variations in TP and TN

Table 1
Results of simple and multiple linear regressions for Heilongjiang Province (TP and TN unit: mg/L).

Variables	Coefficient	*p*	R^2	N	Predicted variable	Predicted range Chl *a* = 5 (μg/L)		
						Fitted value	Upper 90% confidence interval	Lower 90% confidence interval
Annual data								
Intercept (b)	1.839	< 0.001	0.306	85	TP	0.0512	0.0412	0.0614
lgTP	0.883	< 0.001						
Intercept (b)	0.817	< 0.001	0.027	85		–	–	–
lgTN	0.443	0.13						
Intercept (b)	1.85	< 0.001**	0.273	83				
lgTP	0.92	< 0.001**			–	–	–	–
lgTN	−0.347	0.206			–	–	–	–
April to September data								
Intercept (b)	1.758	< 0.001	0.279	82	TP	0.0533	0.0418	0.0656
lgTP	0.832	< 0.001						
Intercept (b)	0.785	< 0.001	0.008	81		–		
lgTN	0.288	0.411						
Intercept (b)	1.727	< 0.001	0.25	80				
lgTP	0.849	< 0.001			–	–	–	–
lgTN	−0.431	0.187			–	–	–	–

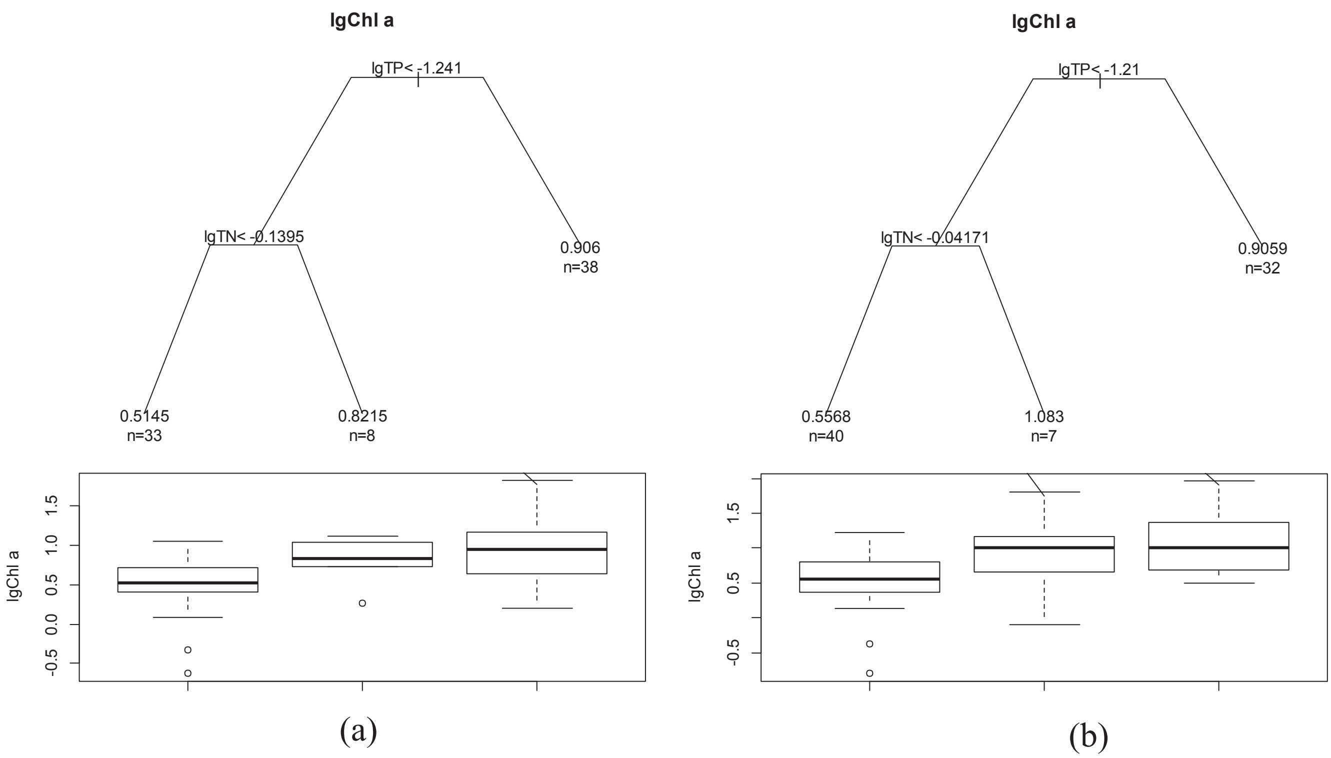


Fig. 3. Regression tree plot of the observed Chl *a* (or lgChl *a*) concentration partitioned with the TN and TP concentrations for Heilongjiang Province.

concentrations in this region must be synergistically controlled to effectively manage water quality.

3.1.3. Changepoint analysis

CPA was applied to verify the CART results for each node in the regression tree. The changepoints, mean and SD of the response variable Chl *a* on both sides of the changepoints were estimated using the nCPA and the BHM methods (Table 2). Uncertainty in the changepoint locations was quantified using the range of the middle 90% of the 1000 bootstrap simulation replicates for the nCPA method and the 90% CIs for the BHM method.

The results from the nCPA method were comparable to those from the BHM method. There were no significant differences between the changepoints identified via the nCPA and BHM methods for TP and TN concentrations, indicating that the probability distribution assumptions for the response variable under the BHM method were appropriate (Table 2). Because the BHM method utilized distributional information for the response variable, it generated narrower CIs for the changepoints (see Table 2) (Qian et al., 2003). If the true probability distribution of the response variable cannot be determined, the nCPA method should be used to confirm the changepoints.

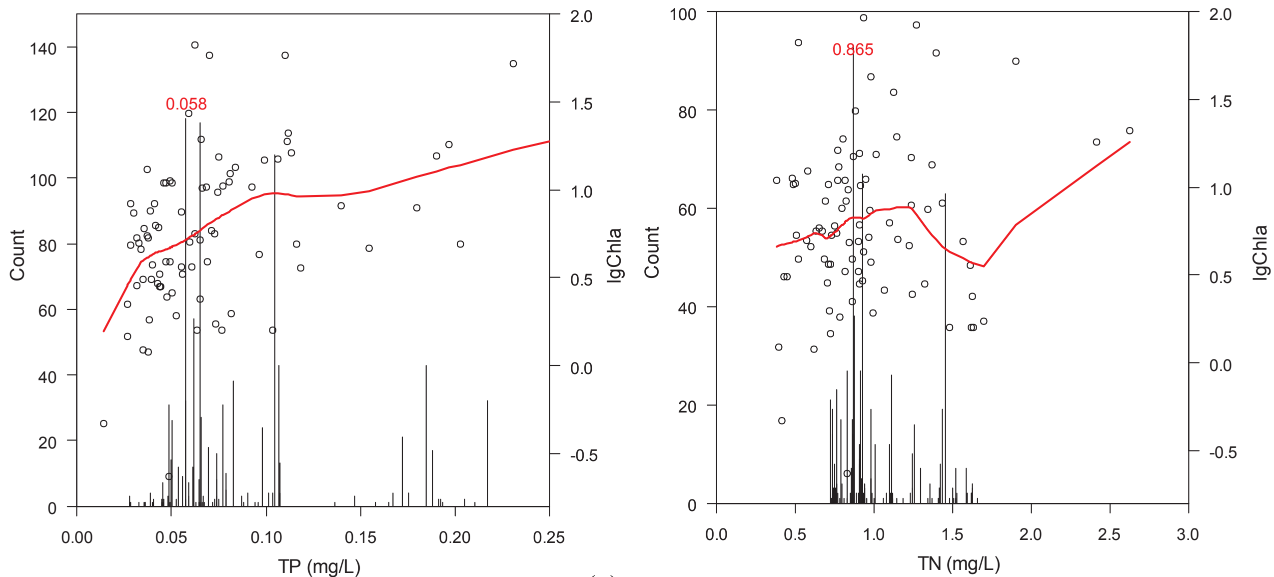
The distributions of TP and TN concentrations, as well as the lgChl *a* concentrations based on the annual data and data from April to September, are illustrated in Fig. 4. The obtained changepoints of TP and TN concentrations from annual data were lower than those obtained from the April to September data. The LOWESS curves and changepoints indicated that Chl *a* concentration decreased until the thresholds were approximately 0.058 (0.060) mg TP/L and 0.865 (0.976) mg TN/L, respectively (Fig. 4).

3.2. Nutrient criteria development with land use-nutrient regression models

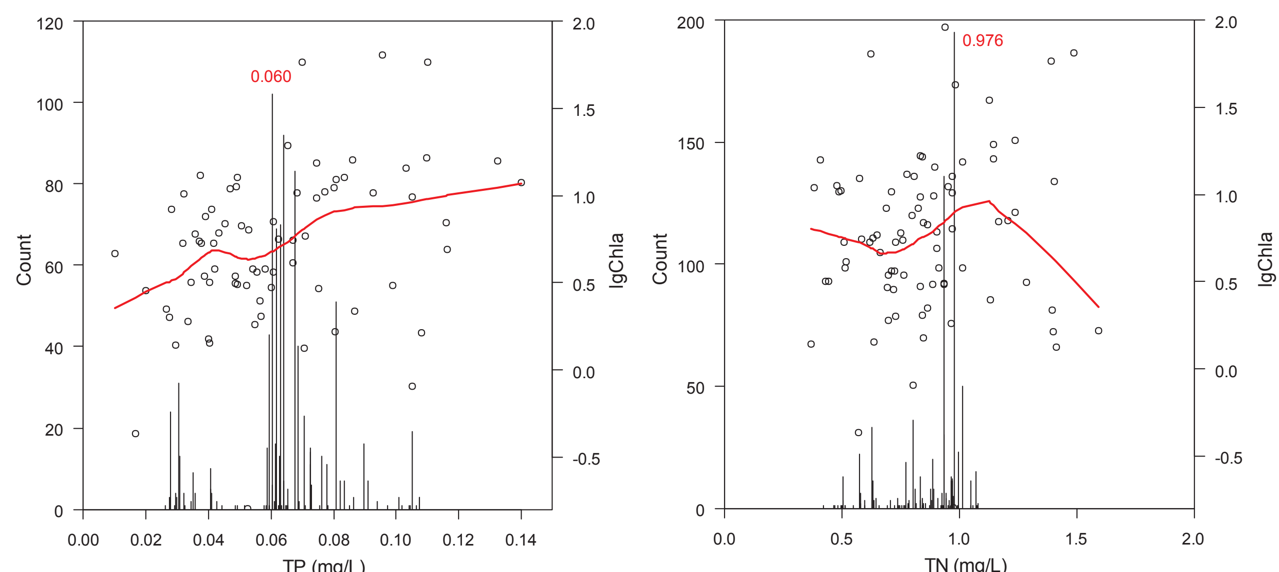
The CART model was employed to identify important land use types that influenced the variations in lgTN, lgTP, and lgChl *a* (Huo et al., 2015b). The regression tree plots of the water quality variables for Heilongjiang Province are presented in Fig. S1 (in the SI). As shown in Fig. S1, forestland was the major land use pattern that affected the Chl *a* and TP concentrations, and an increase in forestland decreased lgChl *a*

Table 2
Threshold values for TP and TN concentrations (mg/L) with the Chl *a* concentrations (μg/L) using the CART, nCPA and BHM methods.

Variables	Data source	CART node point	nCPA			BHM		
			Change -point	Interval	Chl *a* mean[n] ± SE	Change -point	Interval	Chl *a* mean[n] ± SE
TP	Annual data	0.058	0.058	0.049, 0.210	4.876[41] ± 2.294, 16.379[45] ± 2.870	0.056	0.053, 0.103	4.915[40] ± 2.318, 16.095[46] ± 2.870
	April to September data	0.062	0.060	0.031, 0.109	4.817[44] ± 2.321, 13.643[31] ± 2.915	0.061	0.060, 0.067	4.817[44] ± 2.321, 13.643[31] ± 2.915
TN	Annual data	0.725	0.865	0.459, 1.586	7.717[43] ± 2.695, 15.147[42] ± 3.075	0.828	0.538, 1.390	7.979[39] ± 2.795, 14.297[47] ± 2.991
	April to September data	0.908	0.976	0.626, 1.392	8.611[62] ± 2.753, 13.879[19] ± 3.525	0.971	0.575, 1.132	8.611[62] ± 2.753, 13.879[19] ± 3.525



(a)



(b)

Fig. 4. Scatter plots with LOWESS curves (α = 0.5) showing the responses of lgChl *a* to TP and TN concentrations.

and lgTP concentrations. Cultivated land was the major land use pattern that influenced the TN concentration, and an increase in cultivated land area would lead to an increase in the lgTN concentration.

The concentrations of lgTN, lgTP, lgChl *a* and the land use percentages in the 21 lake watersheds were analyzed and used to establish land use-nutrient regression models (Table 3). These regression models were used to determine the relationships among nutrients, lgChl *a*, and land use patterns. All-possible-subset regression with p as an index for selecting the land use models was employed to predict the nutrient and lgChl *a* concentrations The best regression models for the nutrient and lgChl *a* concentrations based on a comparison of R^2 values are summarized in Table 3. The analysis revealed that the regression method generally predicted all studied variables correctly due to the significant relationships among the water quality variables and land use patterns for the lakes sampled in this study ($p < 0.05$). This finding indicates that land use percentages can be used as predictor variables.

As shown in Table 3, lgChl *a* and lgTP are strongly related to PF in the lakes and reservoirs in Heilongjiang Province. This result indicates that larger percentages of forestland have stronger positive influences on the concentrations of lgTP and lgChl *a*. This result can be attributed to the fact that vegetation cover can affect soil properties and overland flow, reduce soil erosion and improve water quality. Cropland accounted for the variability in lgTN because the majority of fertilizers applied in cropland areas can enter the water supply through runoff and increase the nitrogen concentration.

Table 3
Land use regression models and criterion values for nutrient variables and Chl *a*.

Model	R	Sig.	The percentage of land use pattern corresponding changepoint	Predicted value
logChl $a = -0.007^{*}$PF + 1.087	0.552	< 0.001	72.56 (PF)	3.794
logTN = 0.002*PC − 0.197	0.201	< 0.001	41.62 (PC)	0.770
logTP = −0.005*PF − 0.996	0.447	< 0.001	47 (PF)	0.059

Table 4
Statistical analysis of water quality data for terrestrial ecosystems in various health states.

Indicator	Terrestrial ecosystem health assessment grade					
	Excellent		Good		Fair	
	Mean	Standard Deviation	Mean	Standard Deviation	Mean	Standard Deviation
Chl *a* (μg/L)	4.938	0.761	8.847	0.824	9.055	1.435
TP(mg/L)	0.047	0.003	0.084	0.009	0.099	0.011
TN(mg/L)	0.763	0.0296	0.895	0.077	1.123	0.125

The nutrient criteria deduced by the land use regression model were 3.794 μg/L for Chl *a*, 0.770 mg/L for TN, and 0.059 mg/L for TP; these criteria were nearly bracketed by the values derived from the stressor-response model.

3.3. Nutrient criteria verification based on terrestrial ecosystem health

Human activities primarily influence land, and fluctuations in the terrestrial ecosystem exert an important influence on water quality and the development of nutrient criteria. A healthy terrestrial ecosystem can rapidly recover from unexpected disturbances resulting from natural or human activities and is characterized by diversity, complexity and robustness. The health statuses of the terrestrial ecosystems of the 21 investigated lakes and reservoirs are illustrated in Fig. 1. The results of a statistical analysis of the water quality data for terrestrial ecosystems in various health statuses are listed in Table 4. As shown in Table 4, the average concentrations of nutrients and Chl *a* significantly increased with the deterioration of terrestrial ecosystem health. This result illustrates that lake water quality is significantly affected by terrestrial ecosystem health and that the deterioration of the terrestrial ecosystem of a lake significantly influences its water quality.

3.4. Effects of climate change indicators on the development of nutrient criteria

Climate change is an important factor that influences the development of nutrient criteria. Climate variability must be considered to establish scientific and reasonable nutrient criteria. ANCOVA was used to test for significant differences among climate change factors while accounting for the effects of nutrients on Chl *a* and land use variables on water quality. The climate variations were quantified using ANCOVA, in which climate change factors were the categorical predictor and the percentage of anthropogenic land use was the covariate. The results of ANCOVA are listed in Table S2. The significance level was less than 0.05, indicating that the climate change indicators would significantly affect the response relationships between lgTN/lgTP and lgChl *a* and between land use patterns and lgTN/lgTP/lgChl *a*. ANCOVA demonstrated that not all climate change indicators had a significant impact on the nutrient-Chl *a* and land use variable-water quality relationships. For example, Win and Pre had significant influences on the relationships of all models except the lgChl *a*-PF model, and only Tm had a significant influence on the relationship between lgChl *a* and PF. There were significant effects on Tm for the lgTN-PC model and on Rhu for the lgChl *a*-lgTP, lgChl *a*-lgTN, and lgTN-PC models. All the selected climate change indicators markedly influenced the lgTN-PC model.

For the climate change indicators that were significantly different ($p < 0.05$), as determined by ANCOVA, nonlinear regression was used to quantitatively characterize the effects of climate change indicators on the relationships between nutrient and Chl *a* concentrations and between land use and nutrient concentrations (Table 5).

Meteorological data showed that the meteorological factors in Heilongjiang Province significantly changed over the past five decades. The annual Tm of the land surface increased drastically from 1961 to 2016 (Fig. 5(a)). Rhu and Pre slightly increased and exhibited notable interannual fluctuation (Fig. 5(b) and Fig. 5(c)). Additionally, Win significantly decreased ($p < 0.001$) beginning in 1961 (Fig. 5(d)).

The cyanobacterial bloom was negatively correlated with Win and positively correlated with Tm and Rhu (Yang et al., 2016). According to the non-LRMs of lgChl *a*-PF and lgTN-PC, the deduced criteria of Chl *a* and TN should decrease with as increase in Tm, mainly because an increase in Tm would stimulate the deleterious proliferation of planktonic algae and cause the algae to bloom in water. Furthermore, increasing Tm is expected to increase the rate of mineralization of soil nutrients and favor deoxygenation at the lake sediment surface, which releases more nutrients into the water column. Hence, stricter criterion values for nutrient and Chl *a* concentrations should be developed to prevent the eutrophication of water bodies.

There is no known ecological relevance of the relationship between cyanobacterial blooms and humidity, which may be an indirect effect caused by the great influence of wind speed on the humidity at the surface of lakes (Yang et al., 2016).

Rainfall can transport large amounts of nutrients into lakes as nonpoint source pollution that enters lakes via runoff. The rainfall intensity was positively correlated with the TN concentration in rivers flowing into lakes (Zhu et al., 2015). Moreover, the TP concentrations in runoff were correspondingly higher after heavy rainfall but were stable when the rainfall intensity was low (Yang et al., 2016). Wet deposition is another nutrient input path from rainfall and could cause the nutrient concentrations in lakes to increase significantly in a short time. For the lgTP-PF and lgTN-PC models, the concentrations of TP and TN increased as the precipitation increased when the percentages of cropland and forestland were constant.

Low wind speed is an important requisite for the formation of cyanobacterial blooms, which are not conducive to the expansion of algae, lead to the gathering of large quantities of cyanobacteria on the water surface, and result in the breakout of eutrophication. Therefore, weak wind conditions usually results in high surface concentrations of cyanobacterial cells and vast bloom areas. In addition, lake sediments are not easily suspended in the water column under low wind conditions. Nutrients in the sediments are released into the overlying water during sediment resuspension. The nutrient release rates are significantly and positively correlated with the wind speed. Hence, low wind speed in this study led to a decrease in the TN and TP concentrations.

4. Discussion

The numeric nutrient criteria determined using the LRM, CART, nCPA, BHM, land use-nutrient regression models and models based on terrestrial ecosystem health in Heilongjiang Province are listed in Table 6. The Friedman test indicated no significant differences among the nutrient criteria obtained using these various methods ($p > 0.05$). The TN and Chl *a* concentrations obtained using the land use-nutrient regression model were slightly lower than those obtained using the stressor-response models. This result may be because the land use-nutrient regression model could not quantify all sources of anthropogenic influence because such data were not readily available (Huo et al., 2015a; Ma et al., 2016). The atmospheric deposition of nitrogen, for example, can exert a considerable impact on water quality and result in variability in biomass and nutrient variables. The quantitative consideration of other factors, such as atmospheric deposition, animal farms, and point discharges, would improve the accuracy of the model (Huo et al., 2015a; Ma et al., 2016). The incorporation of other anthropogenic sources of nutrient inputs would further improve the reliability of nutrient criteria development.

The LRM, CART, nCPA, BHM, and land use-nutrient regression models and methods based on terrestrial ecosystem health assessment do not require the collection of a large amount of data from reference

Table 5
Nonlinear regression model for the lgChl *a*-lgTP, lgChl *a*-lgTN, lgChl *a*-PF, lgTP-PF, and lgTN-PC relationships.

Nonlinear regression model	R^2	The variation trend of meteorological factors.	The change of criterion values
lgChl *a*-lgTP model			
lgChl *a* = 0.157*lgTP + 0.005*lgTP*Rhu + 0.022*Rhu − 0.059	0.474	Rhu↑	TP↓
lgChl *a* = 1.434*lgTP − 0.416*lgTP*Win − 0.285*Win + 1.992	0.354	Win↓	TP↓
lgChl *a* = 0.427*lgTP + 0.001*Pre + 0.696	0.329	Pre↑	TP↓
lgChl *a* -lgTN model			
lgChl *a* = 0.71*lgTN − 0.009*lgTN*Rhu + 0.015*Rhu − 0.208	0.4	Rhu↑	TN↓
lgChl *a* = 2.378*lgTN − 0.926*lgTN*Win + 0.209*Win + 0.3	0.324	Win↓	TN↓
lgChl *a* = 1.3*lgTN − 0.002*logTN*Pre + 0.001*Pre + 0.289	0.223	Pre↑	TN↓
lgChl *a* -PF model			
lgChl *a* = −0.015*PF + 0.003*PF*Tm − 0.174*Tm + 1.661	0.385	Tm↑	Chla↓
lgTP-PF model			
lgTP = −0.008*PF + 0.001*PF*Win − 0.07*Win − 0.827	0.203	Win↓	TP↓
lgTP = −0.006*PF + 0.00002282*PF*Pre + 0.0000458*Pre − 1.018	0.213	Pre↑	TP↑
lgTN-PC model			
lgTN = 0.006*PC − 0.024*Tm − 0.153	0.135	Tm↑	TN↓
lgTN = −0.03*PC − 0.005c*Rhu + 0.092	0.107	Rhu↑	TN↓
lgTN = 0.033*PC − 0.013*PC*Win + 0.096*Win − 0.414	0.176	Win↓	TN↓
lgTN = −0.01*PC + 0.0000226*PC*Pre − 0.131	0.143	Pre↑	TN↑

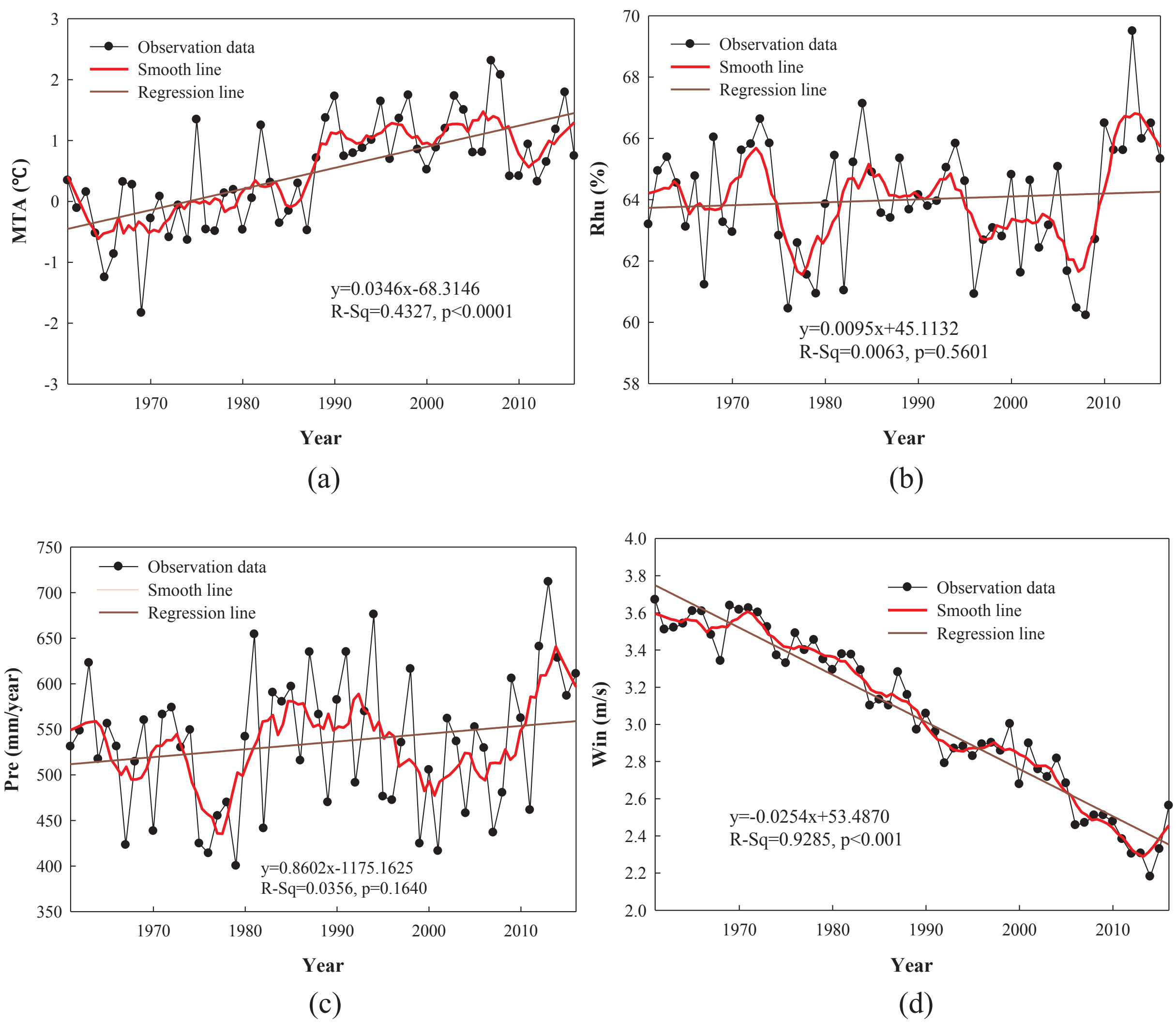


Fig. 5. The mean temperature anomaly of the land surface (MTA, a), annual relative humidity (Rhu, b), annual precipitation (Pre, c), and annual wind speed (Win, d) in Heilongjiang Province from 1961 to 2016.

Table 6
TN, TP, and Chl *a* criteria for Heilongjiang Province determined using various methods.

Method	Data source	TP (mg/L)	TN (mg/L)	Chl *a* (μg/L)
Linear regression model (LRM)	Annual data	0.051	–	5
	April to September data	0.053	–	5
Classification and regression tree analysis (CART)	Annual data	0.058	0.725	4.406
	April to September data	0.062	0.908	4.317
Nonparametric changepoint analysis (nCPA)	Annual data	0.058	0.865	4.876
	April to September data	0.062	0.976	4.817
Bayesian hierarchical model (BHM)	Annual data	0.056	0.828	4.915
	April to September data	0.061	0.971	4.817
Land use-nutrient regression model	Annual data	0.059	0.770	3.794
Based on terrestrial ecosystem health	Annual data	0.047	0.763	4.938

lakes or minimally impacted lakes. The LRM, CART, nCPA, and BHM methods provide estimates of relationships between a response variable and a stressor variable; in this study, TN and TP were chosen as the stressor variables, and Chl *a* was selected as the biological response variable (Huo et al., 2015b; Zhang et al., 2014). In contrast to the LRM method, the CART, nCPA and BHM methods do not require the establishment of a threshold value for the response variable to determine a potential numeric criterion (Huo et al., 2015b) and can thus yield objective criteria. The land use-nutrient regression models presented in this article provide a basis for understanding the impacts of land use changes on water quality and extrapolating the criterion concentrations for water quality protection. The criterion values estimated from the stressor-response model and land use-nutrient regression model were similar to the average values of the corresponding variables under excellent terrestrial ecosystem health. Thus, the average values of water quality variables corresponding to excellent terrestrial ecosystem health can be used as nutrient criteria for the study region. These results will be beneficial for assisting planners and policy makers in estimating the expected changes in water quality as land use changes over time. Moreover, terrestrial ecosystem health assessments are beneficial for understanding the health of terrestrial ecosystems and the degree of interference from human activities.

Climate change and human-based changes in land use have the potential to influence the development of nutrient criteria. One of the mechanisms by which land use and climate affect community and ecosystem properties is by altering biogeochemical cycles. Cultivation requires greater consumption of nutrients than does natural vegetative cover and damages the structure of the soil and the nutrient-rich topsoil, which results in the loss of nutrients and soil particles during rainfall and runoff processes (Gandhi et al., 2008; Gao et al., 2014). Forestland may improve the buffering capacity of soil and the net primary productivity of an ecosystem and plays an important role in intercepting pollutants before they enter water bodies. Increases in the loads of land-based pollutants (e.g., nutrients, sediment, and pesticides) caused by changes in land use during urbanization can result in a decrease in water quality (Álvarez-Romero et al., 2013). An increased percentage of impervious cover can further increase the export of nutrients from watersheds. Thus, the increases in nutrient loading related to land use changes must be evaluated and quantitatively described using models. Evaluations of the relationships between anthropogenic land use and water quality indicators are beneficial for identifying specific anthropogenic land use practices that contribute to nutrient pollution and may help guide management decisions. The integrated planning and management of land use is an effective approach to decreasing nitrogen and phosphorus pollutant concentrations.

Climate change poses a serious additional challenge to formulating nutrient criteria as part of a strategy for controlling blooms (Havens and Paerl, 2015). Climate change mainly includes changes in precipitation, temperature, and wind speed, which have a significant impact on the water quality of lakes and reservoirs. The global climate is projected to warm, leading to increases in the frequency and severity of EWEs in the future, such as heavy rainfall, extreme drought, strong winds, and heavy waves. Heavy rainfall and strong winds may cause algal blooms when all conditions are appropriate (Yang et al., 2016; Zhu et al., 2014). The algal blooms caused by climate change can be mainly attributed to a short-term increase in the nutrient concentrations in lake water induced by EWEs. Strong winds are usually associated with internal nutrient releases from sediments; therefore, lake sediments are an important source of pollution (Yang et al., 2016). The sediments are easily suspended in the water column under strong winds in shallow lakes. A climate-driven change in water temperature would modify the phytoplankton community by supporting bloom-forming cyanobacteria, which favor increased nutrients and higher water temperatures. The longer we wait to take action to control blooms and the more time that climate change has to exert synergistic effects on nutrients, the less likely it becomes that control will be attained (Havens and Paerl, 2015). Hence, climate change should be factored into mitigation strategies for eutrophication and should be considered in the development of nutrient criteria.

Furthermore, with the development of urban, green infrastructures and climate change adaptation policies should be explored to mitigate nutrients loading into aquatic environment. For example, green roofs, as stormwater management technologies, can mitigate the impacts of urbanization on hydrological processes; the reduction of the stormwater through green roof implementation had a positive impact on flood protection (Schmitter et al., 2016). A structured approach for designing climate adaptation policies, based on the concepts of Adaptation Pathways and Real Options Analysis, results in incorporation of flexibility that allows change over time in response to how the future unfolds, what is learned about the system, and changes in societal preferences (Buurman and Babovic, 2016). The approach incorporates flexibility as intelligent decision-making mechanisms that enable systems to avoid incorporate uncertainties, such as amount of rainfall, unit cost of water, and other uncertainties associated with future changes in technological domains (Deng et al., 2013). A framework which combines the process-based models and data assimilation technique could efficiently run offline to directly correct and update the output of water quality models, which can fast and efficiently forecast the variation of water quality indictors as climate change persists (Wang et al., 2016a,b).

5. Conclusion

The criterion values for TN, TP, and Chl *a* were developed based on the combined consideration of stressor-response models, land use-nutrient regression models, and terrestrial ecosystem health using field investigations in Heilongjiang Province. The results suggested that there were no significant differences in the nutrient criteria obtained by the various methods. ANCOVA was used to discern the climate change factors that significantly impacted the relationships between nutrients and Chl *a*, as well as land use and nutrients. Nonlinear regression was used to quantitatively characterize the impact of climate change indicators on the relationships between nutrient and Chl *a* concentrations and between land use and nutrient concentrations. These results indicated that climate change should be considered for the development of nutrient criteria, and with a warmer climate, achieving a desired water quality without the threat of eutrophication in the future will require stricter nutrient criteria than are required under the current climate conditions.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jhydrol.2018.06.039.

References

Álvarez-Romero, J.G., Devlin, M., Silva, E.T.D., Petus, C., Ban, N.C., Pressey, R.L., et al., 2013. A novel approach to model exposure of coastal-marin e eco systems to riverine flood plumes base d on remote sensing techniques. J. Environ. Manage. 119, 194–207.
Bouleau, G., Pont, D., 2015. Did you say reference conditions? Ecological and socio-economic perspectives on the European Water Framework Directive. Environ. Sci. Policy 47, 32–41.
Breiman, L., Friedman, J., Stone, C.J., Olshen, R.A., 1984. Classification and Regression Trees, Wadsworth Statistics/Probability. Chapman & Hall/CRC, London, UK.
Buurman, J., Babovic, V., 2016. Adaptation Pathways and Real Options Analysis: An approach to deep uncertainty in climate change adaptation policies. Policy Soc. 35 (2), 137–150.
Cao, H.S., Kong, F.X., Luo, L.C., Shi, X.L., Yang, Z., Zhang, X.F., et al., 2006. Effects of Wind and Wind-Induced Waves on Vertical Phytoplankton Distribution and Surface Blooms of Microcystis aeruginosa in Lake Taihu. J. Freshwater Ecol. 21 (2), 231–238.
Chen, Y., Tang, D., 2012. Eddy-feature phytoplankton bloom induced by a tropical cyclone in the South China Sea. Int. J. Remote Sens. 33 (23), 7444–7457.
David, M.B., Wall, L.G., Royer, T.V., Tank, J.L., 2006. Denitrification and the nitrogen budget of a reservoir in an agricultural landscape. Ecol. Appl. 16, 2177–2190.
Deng, Y., Cardin, M.A., Babovic, V., Santhanakrishnan, D., Schmitter, P., Meshgi, A., 2013. Valuing flexibilities in the design of urban water management systems. Water Res. 47 (20), 7162–7174.
Dodds, W.K., 2006. Determining Ecoregional reference conditions for nutrients, secchi depth and chlorophyll a in Kansas lakes and reservoirs. Lake Reserv. Manage. 22 (2), 151–159.
Gandhi, B., Puneet, S., Luke, M., Diane, H., Upton, H., 2008. Assessment of economic and water quality impacts of land use change using a simple Bioeconomic model. Environ. Manage. 42, 122–131.
Gao, Y., He, N.P., Yu, G.R., Chen, W.L., Wang, Q.F., 2014. Long-term effects of different land use types on C, N, and P stoichiometry and storage in subtropical ecosystems: a case study in China. Ecol. Eng. 67, 171–181.
Hausmann, S., Charles, D.F., Gerritsen, J., Belton, T.J., 2016. A diatom-based biological condition gradient (BCG) approach for assessing impairment and developing nutrient criteria for streams. Sci. Total Environ. 562, 914–927.
Havens, K.E., Paerl, H.W., 2015. Climate change at a crossroad for control of harmful algal blooms. Environ. Sci. Technol. 49 (21), 12605–12606.
Hawkins, C.P., Olson, J.R., Hill, R.A., 2010. The reference condition: predicting benchmarks for ecological and water-quality assessments. J. N. Am. Benthol. Soc. 29 (1), 312–343.
Hayes, N.M., Vanni, M.J., Horgan, M.J., Renwick, W.H., 2015. Climate and land use interactively affect lake phytoplankton nutrient limitation status. Ecology 96 (2), 392–402.
Henson, S.A., Beaulieu, C., Ilyina, T., John, J.G., Long, M., Séférian, R., et al., 2017. Rapid emergence of climate change in environmental drivers of marine ecosystems. Nat. Commun. 8, 14682.
Huo, S., Ma, C., Xi, B., Gao, R., Deng, X., Jiang, T., et al., 2014. Lake ecoregions and nutrient criteria development in China. Ecol. Indic. 46, 1–10.
Huo, S., Ma, C., He, Z., Xi, B., Su, J., Zhang, L., et al., 2015a. Prediction of physico-chemical variables and chlorophyll a criteria for ecoregion lakes using the ratios of land use to lake depth. Environ. Earth Sci. 74 (5), 3709–3719.
Huo, S., Ma, C., Xi, B., He, Z., Su, J., Wu, F., 2015b. Nonparametric approaches for estimating regional lake nutrient thresholds. Ecol. Indic. 58, 225–234.
Huo, S., Xi, B., Ma, C., Liu, H., 2013. Stressor-response models: a practical application for the development of lake nutrient criteria in China. Environ. Sci. Technol. 47 (21), 11922–11923.
Kissinger, M., Rees, W.E., 2010. Importing terrestrial biocapacity: the U.S. case and global implications. Land Use Policy 27, 589–599.
Kosten, S., Huszar, V.L.M., Bécares, E., Costa, L.S., Donk, E., Hansson, L.A., et al., 2012. Warmer climates boost cyanobacterial dominance in shallow lakes. Global Change Biol. 18 (1), 118–126.
Lamon, E.C., Qian, S.S., 2008. Regional scale stressor-response models in aquatic ecosystems. J. Am. Water Resour. As. 44, 771–781.
Liu, H., 2011. In: Lake Eutrophication Control. China Environmental Science Press, Beijing, pp. 389.
Ma, C., Huo, S., Sun, W., Xi, B., He, Z., Su, J., et al., 2016. Establishment of physico-chemical variables and Chl a criteria based on land-use patterns and terrestrial ecosystem health. Ecol. Eng. 97, 355–362.
National Climate Center, 2016. The Climate Change Monitoring Bulletin in China. National Climate Center, Beijing.
Paerl, H.W., Huisman, J., 2009. Climate change: a catalyst for global expansion of harmful cyanobacterial blooms. Env. Microbiol. Rep. 1, 27–37.
Paerl, H.W., Paul, V.J., 2012. Climate change: links to global expansion of harmful cyanobacteria. Water Res. 46 (5), 1349–1363.
Prc, M.E.P., 2002. Water and Wastewater Monitoring and Analysis Methods. China Environmental Science Press, Beijing.
PRC MEP, 2013. The technique guide of watershed ecosystem health assessment (For trial implementation). http://www.docin.com/p-930708583.html. 2016.04.155. (In Chinese).
Qian, S., 2009. Environmental and Ecological Statistics with R. Chapman & Hall/CRC, London, British.
Qian, S., Anderson, C., 1999. Exploring factors controlling the variability of pesticide concentrations in the willamette river basin using treebased models. Environ. Sci. Technol 33, 3332–3340.
Qian, S.S., King, R.S., Richardson, C.J., 2003. Two statistical methods for the detection of environmental thresholds. Ecol. Model. 166 (1–2), 87–97.
Qian, S.S., Pan, Y., King, R.S., 2004. Soil total phosphorus threshold in the Everglades: a Bayesian changepoint analysis for multinomial response data. Ecol. Indic. 4 (1), 29–37.
Reichwaldt, E.S., Ghadouani, A., 2012. Effects of rainfall patterns on toxic cyanobacterial blooms in a changing climate: Between simplistic scenarios and complex dynamics. Water Res. 46 (5), 1372–1393.
Robson, B.J., Hamilton, D.P., 2003. Summer flow event induces a cyanobacterial bloom in a seasonal Western Australian estuary. Mar. Freshwater Res. 54 (2), 139–151.
Schmitter, P., Goedbloed, Albert, Galelli, S., Babovic, V., 2016. Effect of catchment-scale green roof deployment on stormwater generation and reuse in a tropical city. J. Water Res. Plan. Man. 142 (7), 05016002.
Sun, W., Huo, S., Ma, C., Xi, B., He, Z., Zhang, J., et al., 2017. Estimating nutrient criteria of the lakes and reservoirs by reference condition approach and stressor-response models. Desalin. Water Treat. 79, 161–177.
US EPA, 2000. Nutrient criteria technical guidance manual: lakes and reservoirs. EPA-822-B-00-001, United States Environment Protection Agency, Office of Water, Washington, DC.
US EPA, 2010. Using Stressor-response Relationships to Derive Numeric Nutrient Criteria. U.S. Environmental Protection Agency, Office of Water, Washington DC.
Van Rompaey, A., Krasa, J., Dostal, T., 2007. Modelling the impact of land cover changes in the Czech Republic on sediment delivery. Land Use Policy 24 (3), 576–583.
Wang, J., Pan, F., Soininen, J., Heino, J., Shen, J., 2016a. Nutrient enrichment modifies temperature-biodiversity relationships in large-scale field experiments. Nat. Commun. 7, 13960.
Wang, X., Zhang, J.J., Babovic, V., 2016b. Improving real-time forecasting of water quality indicators with combination of process-based models and data assimilation technique. Ecol. Indic. 66, 428–439.
Wu, J., Gao, X., 2013. A gridded daily observation dataset over China region and comparison with the other datasets. Chinese J. Geophys. 56 (4), 1102–1111.
Wu, T., Qin, B., Brookes, J.D., Shi, K., Zhu, G., Zhu, M., et al., 2015. The influence of changes in wind patterns on the areal extension of surface cyanobacterial blooms in a large shallow lake in China. Sci. Total Environ. 518–519, 24–30.
Xu, Y., Gao, X., Shen, Y., Xu, C., Shi, Y., Giorgi, F., 2009. A daily temperature dataset over China and its application in validating a RCM simulation. Adv. Atmos. Sci. 26 (4), 763–772.
Yang, Z., Zhang, M., Shi, X., Kong, F., Ma, R., Yu, Y., 2016. Nutrient reduction magnifies the impact of extreme weather on cyanobacterial bloom formation in large shallow Lake Taihu (China). Water Res. 103, 302–310.
Zhang, W.W., Li, H., Sun, D.F., Zhou, L.D., 2012. A Statistical Assessment of the Impact of Agricultural Land Use Intensity on Regional Surface Water Quality at Multiple Scales. Int. J. Env. Res. Pub. He. 9, 4170–4186.
Zhang, Y., Huo, S., Ma, C., Xi, B., Li, X., Liu, H., 2014. Using Stressor-Response Models to Derive Numeric Nutrient Criteria for Lakes in the Eastern Plain Ecoregion, China. Clean – Soil, Air, Water 42 (11), 1509–1517.
Zhu, M., Paerl, H.W., Zhu, G., Wu, T., Li, W., Shi, K., et al., 2014. The role of tropical cyclones in stimulating cyanobacterial (Microcystis spp.) blooms in hypertrophic Lake Taihu. China. Harmful algae 39, 310–321.
Zhu, Q.D., Sun, J.H., Hua, G.F., Wang, J.H., Wang, H., 2015. Runoff characteristics and non-point source pollution analysis in the Taihu Lake Basin: a case study of the town of Xueyan. China. Environ. Sci. Pollut. R 22 (19), 15029–15036.